

Characterizing spatial uncertainty when integrating social data in conservation planning

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Running title: Social data spatial uncertainty

Keywords: social research, elicited values, conservation planning, conservation opportunity, systematic conservation assessment, spatial uncertainty, spatial data quality, public participation GIS

Abstract

Recent conservation planning studies have presented approaches for integrating spatially referenced social (SRS) data with a view to improving the feasibility of conservation action. We reviewed the growing conservation literature on SRS data, focusing on elicited or stated preferences derived through social survey methods such as choice experiments and public participation geographic information systems. Elicited SRS data includes the spatial distribution of willingness to sell, willingness to pay, willingness to act, and assessments of social and cultural values. We developed a typology for assessing elicited SRS data uncertainty which describes how social survey uncertainty propagates when projected spatially and the importance of accounting for spatial uncertainty such as scale effects and data quality. These uncertainties will propagate when elicited SRS data is integrated with biophysical data for conservation planning and may have important consequences for assessing the feasibility of conservation actions. To explore this issue further, we conducted a systematic review of the elicited SRS data literature. We found that social survey uncertainty was commonly tested for, but that these uncertainties were ignored when projected spatially. Based on these results we developed a framework which will help researchers and practitioners estimate social survey uncertainty and use these quantitative estimates to systematically address uncertainty within an analysis. This is important when using SRS data in conservation applications because decisions need to be made irrespective of data quality and well characterized uncertainty can be incorporated into decision theoretic approaches.

Introduction

One of the great challenges to conservation planning is accounting for the feasibility of conservation actions, which requires an understanding of the complex social, economic and institutional environments in which conservation occurs (Knight et al. 2006). Recent conservation planning studies have presented tools for utilizing mapped quantitative social data with the view towards quantifying opportunities for conservation interventions. While tools for assessing conservation opportunities have considered social and cultural values (Brown 2012), governance characteristics (Mills et al. 2013) and self-reported behavior (Curtis et al. 2005; Raymond & Brown 2011) these tools rarely consider the uncertainties associated with mapping these attributes. This can have the perverse result of recommending actions that have neutral or even negative conservation outcomes.

There are numerous methods for deriving mapped social data for conservation planning. These range from modeling preferences based on land use (Goldberg et al. 2011), property prices (Polyakov et al. 2014) or travel costs (Van Berkel & Verburg 2014) to implicitly integrating social values using interactive GIS software (Lesslie 2012) (Figure 1). We focused on a subset of those methods where data on elicited or stated preferences are derived through social science survey methods which could be or are used directly in a spatial context for conservation planning. Social survey methods include the use of survey techniques to assess general community values, attitudes and beliefs (see Babbie [2007] for an overview), and the use of public participation GIS (PPGIS) to assess place-based values and preferences (e.g., Brown 2005), and choice experiment (e.g. Campbell et al. 2009) (Figure 1). Hereafter we refer to data collected and then mapped derived from elicited social survey methods for conservation planning as elicited spatially referenced social (SRS) data. These methods are used in the majority of research where mapped social data are incorporated into conservation planning.

Given that the use of elicited SRS data within conservation planning is a growing area of research, it is an opportune time to evaluate the methods and associated uncertainty that results from the use of mapped social data in conservation planning. In broad terms, we

define uncertainty as sources of uncertainty within the inputs, outputs and analysis that may be: measurable (e.g. GPS error); related to difficult to define concepts; related to future events that are difficult to predict; and uncertainty in models associated with a lack of knowledge or due to generalisations (see extended definition in Supporting Information). In the social sciences, the uncertainties associated with the collation of social data are well documented and include measurement validity, response bias and representativeness (Hair et al. 2009; Haslam & McGarty 2001). Further, the spatial and ecological sciences have characterized a suite of uncertainties associated with mapping and modeling of spatial data, including scale issues and classification error (Devillers & Jeansoulin 2010; Lechner et al. 2012a; Rocchini et al. 2012).

Uncertainty in SRS data is especially concerning because it can compound existing uncertainty present within biophysical data such as species distribution models and when used within systematic conservation planning (SCP) tools. Combining SRS data with biophysical data may result in greater levels of uncertainty as these multiple forms of uncertainty may interact (e.g. Lechner et al. 2013) and multiply (e.g. Langford et al. 2011). For example, using simulated data Visconti et al. (2010) found that data on vulnerability to habitat loss should only be included in SCP when uncertainty in this data is <20-30%. They showed that with greater uncertainty it was counterproductive to utilize this data and better results could be obtained using biodiversity value alone. A key motivation for including SRS data is to make plans more implementable, but data uncertainty could result in less accurate or implementable plans - the direct opposite of the desired outcome.

We addressed the question of how to manage uncertainties in SRS data by identifying the types of social data analyzed and the common types of geospatial processing methods used for creating elicited SRS data; developing a typology of SRS data uncertainty based on a review of the types of uncertainty identified in the social and spatial science literatures associated with the social survey and geospatial methods used; reviewing whether existing conservation planning studies are addressing SRS data uncertainty as defined by the typology; and using the results of the reviews to develop a process for more effectively managing uncertainty issues in future conservation planning studies. We also considered research directions required to systematically address these uncertainties and the implications this has for conservation planning in general.

Geospatial methods for deriving elicited SRS data

We focused specifically on elicited SRS data which meets all the following criteria: one of the final outputs is a map describing individual preferences elicited directly through social science survey methods for use in conservation planning; mapping outputs aim to characterize the whole of the study area; and there is a potential for these mapped outputs to be integrated with spatially explicit biophysical data for use within SCP (e.g. Zonation [Moilanen et al. 2011]).

Three broad methods for eliciting social data are commonly used for deriving elicited SRS data: public participation GIS (PPGIS), choice experiments, and standard survey methods. The PPGIS is a suite of techniques for engaging local communities through the use of a GIS whereby participants locate points or regions on maps describing values related to conservation outcomes (Brown 2012). In contrast, a choice experiment is a survey technique where respondents are asked to choose between different bundles of (environmental) goods, which are described in terms of their attributes, or characteristics, and the levels that these attributes take (Adamowicz 2004; Hanley et al. 1998). By a standard survey we mean commonly applied methods of eliciting information through questionnaires or interviews.

A range of geospatial and statistical methods can be used to spatially project elicited social data for integration with biophysical data (Table 1). These methods have been used to

map social data including the perceptual values individuals associate with landscapes (e.g. Campbell et al. 2009; Raymond et al. 2009) and stated preferences which describe the preference for products and services such as willingness to pay (WTP), collaborate, or sell for conservation (e.g. Curran et al. 2012; Knight et al. 2010). Spatial layers using data of perceptual values are produced using a range of processing methods based on geographic units defined either by a raster grid or areal boundary (Table 1: geospatial methods 2 and 4). In contrast, stated preferences in some cases requires no geospatial processing as individual social data are linked directly to their spatial locations (such as owners properties; Table 1: geospatial method 1). Stated preferences may also require interpolation to map preferences in areas where there is no data. This is done using a range of statistical methods such as predictive (e.g. Brouwer et al. 2010; Table 1: geospatial method 3) and Kriging (e.g. Campbell et al. 2009; Table 1: geospatial method 5).

Typology for assessing SRS data uncertainty

We developed a typology for assessing SRS data uncertainty by synthesizing insights from the social science and spatial science literatures with respect to the range of geospatial methods used for deriving these data and integrating the data within analysis. The typology describes uncertainties associated with: the collation and interpretation of social data; the projection of social data spatially; and the integration of elicited SRS data with other data sources such as biophysical data.

The many different forms of uncertainty in the social sciences have been eloquently categorized in a paper by Haslam and McGarty (2001) into internal and external methodological uncertainties (Table 2), in addition to statistical uncertainty. Internal methodological uncertainty is related to whether an observed effect has been correctly measured and interpreted (Hair et al. 2009) and depends on face validity, content validity, and construct validity (Table 2). External methodological uncertainty arises when researchers are unsure whether results can be generalized to the wider population of interest. It requires a consideration of the sampling strategy, sample size, representativeness of the sample and associated non-response bias. A more detailed discussion of social survey methods uncertainty and methods to address it are in Supporting Information.

When projecting social data spatially, the methodological uncertainty associated with social surveys can be considered in the same way as data accuracy within spatial models in terms of uncertainty propagation. Social survey data accuracy can be measured as the deviation from the true value (e.g. the deviation from the correct value of WTP estimated for an individual on a property). Data accuracy is a general aspect of a suite of uncertainty sources known as data quality (Devillers & Jeansoulin 2010; Shi 2010). Data quality considerations include, but are not limited to: completeness, logical consistency, positional accuracy, temporal accuracy, thematic accuracy, coverage, lineage, accessibility, and interpretability (Aspinall & Pearson 1996; Devillers & Jeansoulin 2010; Shi 2010). Uncertainty associated with data quality has unique characteristics when considered in space. For example, as error is spatially distributed across the landscape, it can magnify when combined with other data or when used in a model (Congalton 1988; Gergel et al. 2007; Heuvelink et al. 1989).

Sources of uncertainty that are specific only to spatial data principally arise from the modifiable areal unit problem (MAUP) (also known as the zoning effect or scaling problem) and the related ecological inference problem and change of support problem (COSP; (Gotway & Young 2002; Openshaw 1984)) (Table 3). The MAUP results from the many ways in which non-overlapping spatial units can be used to divide a study area for the purposes of analyses such as a raster grid or census district boundaries (Openshaw 1984). While COSP is a broader term referring to changing the types, size and shape of the spatial

units within any single study e.g. point, lines, areas and pixel (Dungan et al. 2002; Gotway & Young 2002). The ecological inference problem (also known as the ecological fallacy) is a specific case of the COSP that is the result of making conclusions about individuals based only on analysis of aggregated data (e.g. at the district level) (King 1997). Whenever social survey data is projected spatially the choice of spatial units in terms of their size and shape (e.g. property boundary, grid cell, catchment) and the relationship with the spatial patterns of the social value or perception being represented will impact on spatial analysis and in some cases render the outputs meaningless (Jelinski & Wu 1996; Lechner et al. 2012b; Openshaw 1984; Wu et al. 1997). In any single analysis there will potentially be multiple sources of the COSP (which includes the MAUP and the ecological inference problem) along with data quality associated uncertainty which together affect both modeling and inference undertaken with the data (Gotway & Young 2002). An extended discussion of COSP and data quality uncertainty and methods to address them can be found in supporting information.

When using elicited SRS data for conservation planning, other types of data such as biophysical data (e.g. land cover and species distributions maps and spatial information on threats and costs) are required and all contain uncertainty. In the case of species' distribution modeling, uncertainties originate from both input data and the process of mapping the species distributions (Elith et al. 2002; Rocchini et al. 2012). Along with SRS data uncertainty, these other sources of uncertainty need to be addressed when conducting analysis.

Based on the geospatial, ecological, and social science literature we have devised a typology that describes the propagation and sources of uncertainty resulting from projecting elicited SRS data spatially and utilizing it within an analysis (Figure 2). Uncertainty first arises in the social survey data due to methodological uncertainty (Figure 2a: non-spatial uncertainty). This social data can then be used in a broad range of ways to map elicited SRS data resulting in uncertainty being propagated to other parts of the analysis. The simplest method of using the social data is to convert to a spatial unit based on the geolocation of the social data (Table 1: geospatial methods 1, 2, and 5). This results in uncertainty taking on a spatial dimension, whereby uncertainty can be treated as classification accuracy (Figure 2b: classification accuracy) (e.g. transcription error). These uncertainties interact with uncertainty that arises from data quality (e.g. transcription error), choice of spatial units and the method for aggregating the data (e.g. average value for a raster cell) (Figure 2b: Data quality and COSP). Alternatively, social survey data uncertainty can affect the analysis as an input into a statistical model when using other elicited SRS data geospatial methods (e.g. Table 1: geospatial methods 3 and 4). Regardless of how uncertainty arises in elicited SRS data (Figure 2c), it will propagate when combined with other forms of data and potentially interact if that data also includes uncertainty (Figure 2d). Additional error will also arise in studies that use statistical analyses even if the social data is 100% accurate due to sample error, model choice, generalizability, etc. We did not consider the mechanisms associated with a statistical analysis because these forms of uncertainty are common to most scientific studies. All the uncertainties associated with the production and analysis of elicited SRS data will be present in the final modeling or mapping output used in conservation planning (Figure 2e).

Review of elicited SRS data literature

We reviewed a subset of the literature on elicited SRS data in order to summarize what social data is being mapped and the geospatial methods used and assess whether uncertainty is being addressed. We identified 16 papers in our systematic review as meeting the criteria for elicited SRS data described above from a Web of Science keywords search ("*conservation planning*" OR "*systematic conservation planning*" OR "*spatial prioritization*") AND Topic = ("*willingness to sell*" OR "*willingness to participate*" OR "*willingness*" OR "*conservation opportunity*" OR "*social value*" OR "*preference*") we conducted in October

2013. We also asked participants attending a workshop on conservation opportunity to identify potential papers (see Supporting Information for full description). The studies reviewed included a broad range of conservation objectives, methods, and environments. Conservation objectives included improving water quality (Brouwer et al. 2010), managing ecosystem services (Bryan et al. 2010), and designing protected area networks (Guerrero et al. 2010) (Table 4) and included a range of environments including both terrestrial and marine. Social data were gathered using interviews, mail surveys and web-based surveys with sample sizes ranging from 29 (Curran et al. 2012) to 766 individuals (Campbell et al. 2009) (Table 4) and response rates, where reported, (10 of 16 studies) ranged from 11.6% to 100%. The size of the study areas ranged from small local scale (Curran et al. 2012) to country-wide (Campbell et al. 2009).

We categorized the studies into three groups based on use of similar social survey and geospatial methods. The first group was individual property owners, in which the likelihood of undertaking a conservation related action on the respondent's property was measured directly (Table 4; Geospatial method: "Areal data descriptive individual's property") based on "willingness to steward" (Pasquini et al. 2010) or "willingness to sell" (Knight et al. 2010). These studies commonly used interview survey techniques with small sample sizes ($n \sim 50$) but with large response rates (89%-100%), indicating high or complete coverage of the relevant stakeholders. The second group of studies was the choice survey group, which included only two studies (Brouwer et al. 2010; Campbell et al. 2009). They both attempted to measure the likelihood of paying for conservation actions with choice survey methods. This group included the two largest sample sizes ($n \sim 700$), which reflects the large data requirements for this experimental approach. The third group was the PPGIS group and included 9 out of 16 studies. They measured collective perceptions of biological importance (or value) (Brown et al. 2004; Raymond et al. 2009; Whitehead et al. 2014). These studies were commonly undertaken at the regional scale involving large sample sizes ($n = 54$ to 500) with moderate response rates (11.6% to 100%) and used PPGIS methods (Table 4).

The geospatial methods used in each study were influenced by the method used to gather social data and by the size of the study area because it is impractical for studies that occur over large areas to sample the total population. The most common geoprocessing method was based on PPGIS (9 out of 16 studies) (Table 4). These PPGIS studies assumed that collective measures of community perceptions of biological importance (or value), or threats to values, were directly related to conservation actions. Our review also included two examples where statistical methods were applied to mapping social data. Brouwer et al. (2010) used a statistical model to assess willingness-to-pay for water quality improvements for sub-basins across a river basin, while Campbell et al. (2009) used the geostatistical Kriging techniques to interpolate between sampled locations to produce a "WTP for landscape improvement" surface.

Social survey uncertainty

Two thirds of the studies reviewed (69%) conducted some kind of assessment of social data uncertainty (see table 4; figure 2a), however, the type of tests used differed between studies. Most commonly, studies with large sample sizes (PPGIS group) but low to moderate response rate assessed the representativeness of the sample size used. Alternatively, those studies that had small sample sizes (individual property owners group) but complete coverage of the targeted group (e.g. total sample) such as Curran et al. (2012) and Knight et al. (2006) tested for internal methodological uncertainty such as construct validity (extent to which a test measures what it is designed to measure) and reliability. Such analyses enabled the systematic identification of different dimensions of conservation opportunity, with the view towards applying and externally validating them in other study areas. In these studies

there is no need to test for sample bias or representativeness as it is assumed that the total population has been sampled (e.g. all relevant landholders). These smaller studies also tended to have a larger number of response variables derived from long questionnaires and thus have more options for testing construct validity. For example, Knight et al.'s (2010) questionnaire had 165 questions that were then reduced to 12 factors.

The PPGIS and choice survey studies have a greater range of uncertainty sources because they don't sample the total population and also aggregate data unlike the individual property owners group. The PPGIS and choice survey studies commonly tested for external methodological uncertainty such as respondent bias. However, they did not test for internal methodological uncertainty (such as construct validity), most likely due to the paucity of response data (e.g. short questionnaires) that is a result of the practical difficulty in gathering more data using this method. For example, PPGIS techniques are commonly conducted at the regional scale and are more time consuming because survey respondents are asked to plot their values on a map. In contrast, the individual property owners group is likely to be more robust to internal methodological uncertainty as this method commonly uses a total sample and have longer questionnaires (describing multiple constructs with redundant questions for the same construct), however, due to small sample sizes and small extents this method will suffer from external methodological uncertainty related to the difficulty in generalizing outside of their study area.

Spatial uncertainty

Uncertainty associated with the creation of elicited SRS data is dependent on the spatial data types and processing methods used - specifically point data inputs represented spatially as areal data (Table 1: geospatial methods 2, 4, and 5) and areal data derived from statistical analysis (Table 1: geospatial method 3). For geospatial method 1 (Table 1), individual social data are linked to property locations and the sources of spatial uncertainty are likely to be insignificant. In contrast, PPGIS methods often start as social value data associated with a point location, which are then aggregated to a grid. Each geospatial process has the potential for uncertainty (see table 3; figure 2b).

In contrast to social data uncertainty only 2 out of 16 studies tested for spatial uncertainty (Table 4). Raymond and Brown's (2006) PPGIS study assessed differences in the outcome of their analysis depending on whether a vector or raster model was used to aggregate the data – an example of testing for issues resulting from the MAUP (and thus the COSP). Campbell et al. (2009) assessed the error of the Kriging estimates, a common output produced using this type of analysis. The group individual property owners is likely to be relatively unaffected by spatial error such as those associated with the COSP because individual respondents provide information about their own property. The COSP do not pose a problem because no aggregation takes place, but there is potential for data quality uncertainty issues.

Uncertainty propagation

No study attempted to understand how the uncertainty in the SRS data propagated (figure 2c and 2d). This would have affected all studies to varying degrees due to uncertainty associated with combining elicited SRS data (figure 2c) with other spatial data (figure 2d). In many cases, social data were integrated with biophysical data (such as biodiversity surrogates) through overlaying both datasets and identifying patterns in the overlap between biophysical values and social values for conservation. Integration with SCP tools was undertaken in four of the papers reviewed including one PPGIS study and three individual property owners group study (Table 4). In each of these cases uncertainty was not tested.

Framework for managing uncertainty

Based on the typology of elicited SRS data uncertainty and the literature review, we propose a framework for more effectively managing uncertainty in the production and use of elicited SRS data. Our framework describes a process that can account for the range of geoprocessing methods and social data types discussed here, but we acknowledge that the technical methods for the management of uncertainty is often context specific and data dependent.

Our framework presents two possible pathways for addressing uncertainty. The first pathway describes the most common currently used approach for addressing uncertainty (figure 3a), but for the second pathway we propose a new method based on integrating existing geospatial methods for addressing social survey uncertainty (figure 3b). The current standard practice in social science is assessing fitness for use for methodological uncertainty as opposed to quantifying uncertainty and deriving estimates of its distribution (see figure 3a). The fitness for use method rejects data if not up to a standard. In cases where data are not fit for use more data are acquired or research questions may be abandoned. Even if some uncertainty is observed (but not beyond levels that is considered unusable), the data are, in most cases, used as if they were 100% accurate (Figure 3a). The assessment of the levels of uncertainty that are appropriate is also generally expert based.

There were no examples in the papers we reviewed where the uncertainty in the social survey was carried over into analysis. Yet, two-thirds of the papers reviewed described some kind of assessment of social survey methodological uncertainty (Table 4). This suggests those papers assessed fitness for use but ignored social survey uncertainty when projecting the social data spatially and/or when using the projected data in further analysis. Furthermore, the standard method for producing and analyzing elicited SRS data issues in most cases failed to account for any forms of spatial uncertainty such as data quality, the COSP and uncertainty propagation (except for 2 of the papers reviewed).

Our proposed process requires that social survey methodological uncertainty are quantitative (Figure 3b) rather than only an assessment of fitness for use. This will require social scientists to build on existing methods for assessing fitness for use and explicitly quantify uncertainty. There is a need to derive reasonable estimates on the bounds of uncertainty when using social science survey methods. As such, social survey uncertainty can be interpreted as a form of data accuracy that can be quantified and addressed using a number of existing methods within the spatial sciences such as sensitivity analysis (see next section). Importantly, the quantification of uncertainty allows us to explicitly account for it in conservation planning (Carvalho et al. 2011; Williams & Johnson 2013) and therefore provides significant advantages over the fit for use approach.

Along with the quantification of social survey method uncertainty, there is a need to address the COSP because all spatial processing methods we identified (especially processing methods 2-4; Table 2) were commonly projected spatially with arbitrary geographic units that were not statistically determined (administrative boundaries, catchment boundaries). Uncertainty can then propagate as a result of projecting the social survey data spatially (Figure 2; arrow B) and from combining it with other datasets that also contain uncertainty (Figure 2; arrow A). Figure 3 suggests that social survey uncertainty needs to be tested in conjunction with the COSP effects as this form of uncertainty will potentially magnify existing uncertainties. Uncertainty also increases with the number of input datasets and the complexity of models. Finally, along with the output maps of social values or conservation priorities, there needs to be a corresponding map that describes the spatial distribution of uncertainty.

Quantifying uncertainty in social data

In the social sciences, no procedures have ever been agreed upon for measuring or estimating methodological uncertainty; however, a lot is known about how to minimize methodological uncertainty (see above and Supporting Information). For example, internal methodological uncertainty can be addressed through appropriate validation of measures while external methodological uncertainty can be reduced through appropriate sampling and the development of social science theory. Figure 3 clearly illustrates the need for the employment of specific tests of internal and external methodological uncertainty on the social data to derive the quantitative estimates that can be assessed within an analysis using accuracy assessment methods. The development of these methods is a fertile ground for further research and will allow for the quantification of uncertainty arising from these sources.

Estimating and addressing uncertainty

Depending on the social data, biophysical data, and geospatial methods, there are numerous approaches for addressing uncertainty. Methods for addressing specific forms of uncertainty are outlined in Supporting Information; however, a common method for quantifying all forms of uncertainty involves testing the contribution of varying model inputs (such as mapped data layers) to variation in the model output, known as sensitivity and uncertainty analysis. These methods can be used for testing all forms of mapping and modeling uncertainty (Crosetto et al. 2000). A common approach for spatial data is to use Monte Carlo simulation methods whereby each uncertainty source is treated as having a probability density function (PDF) with a known mean and variance for each spatial object (e.g. point, pixel or area), then values are randomly drawing from the PDF and the analysis is rerun with different values for each spatial object to produce confidence bounds (Burrough & McDonnell 1998). Variations on this method include testing for the interaction of uncertainty sources (Saltelli & Annoni 2010) and modeling error in more realistic ways by incorporating the spatial distribution of error (Congalton 1988; Heuvelink 2002). Such methods could be used to develop confidence bounds for social data prior to integration with biophysical data. The inclusion of quantified social uncertainties through this method (or similar) within elicited SRS data analysis is the fundamental difference between current approaches used in the studies we reviewed and our proposed approach (Fig. 3).

Testing for the COSP sensitivity in the creation of elicited SRS data or combining elicited SRS data within a model can be achieved by simulating multiple zoning and scale configurations. This method is a useful first step; however, it is difficult to test for the COSP in a probabilistic way because there are infinite ways to modify spatial boundaries or aggregate data, thus more sophisticated approaches may potentially be used. Testing for this kind of uncertainty should be done for most elicited SRS mapping tasks (except for individual property data) and for all studies that integrate these data with biophysical data.

In many cases, complex methods will be required if a sensitivity analysis demonstrates high levels of scale dependent uncertainty. Some of these methods for addressing uncertainty are specific to one of the four different geospatial processing methods and some are more generally applicable. A summary of potential methods that can be applied for addressing specific kinds of the COSP can be found in supporting information. These methods range from geostatistical treatments (Gotway & Young 2002) to use of cross-classification with other socio-demographic variables (e.g., sex, race) to address the ecological inference problem (King 1997).

Implications of uncertainty

In conservation, decisions need to be made even when uncertainty is large. Yet, if these uncertainties can be quantified, decision theoretic approaches can be used to deal with them.

Building on previous enquiry (Burgman et al. 2005), we argue the explicit treatment of spatial uncertainty in SRS data needs to become routine and should use the approach outlined in Figure 3b instead of the current fitness for use approach (e.g. Figure 3a). The choice of the methods used for including social data and assessing uncertainty within conservation planning will depend on resources, the complexity of the study area, and its size. However, addressing spatial uncertainty and uncertainty propagation is rarely undertaken and can be challenging for workers without significant expertise in GIS, statistics, and writing source code (Devillers et al. 2010; Heuvelink 2002). For example, it is rare for a map to explicitly represent uncertainty in spatial data (Schmit et al. 2006). The difficulty of addressing uncertainty is compounded by numerous forms of uncertainty that have been identified, making it challenging to analyze the consequences of each (Chen 2008; Devillers et al. 2010; King et al. 2004; Lechner et al. 2012a).

Uncertainty associated with SRS data should be rigorously assessed to ensure that the benefits of including social data into conservation planning outweigh the impact of adding additional sources of uncertainty. Existing literature on systematic conservation planning indicates that the most variable data included will tend to drive the conservation priorities identified and this is most commonly the socioeconomic data (Bode et al. 2008; Ferraro 2003). However, given that existing uncertainties associated with spatial data as SCP inputs are often not adequately dealt with (Langford et al. 2011; Visconti et al. 2010), it is important to weigh up the benefits and costs of incorporating this uncertain SRS data into conservation planning (Tulloch et al. this issue).

Value of information theory can be used to explicitly evaluate the degree to which the current SRS data (or additional SRS data) will reduce uncertainty and improve conservation decisions (Forsberg & Guttormsen 2006; Raiffa & Schlaifer 2000; Yokota & Thompson 2004). Social data are collected with the expectation they will reduce uncertainty about cost, feasibility, and opportunities. However, if cost of collecting that data exceeds the value of that information because uncertainty levels are high, it may be better to not invest in that social data. Quantifying uncertainty in SRS data and then undertaking a value of information analysis can help us make this decision from a conservation planning perspective. Most of the papers in the peer reviewed literature on SRS data are theoretical in nature, and it is not yet possible to assess whether the inclusion of social data have made planning more implementable.

When seeking to apply the uncertainty measurements derived from the process outlined in Figure 3b, conservation planners should consider how this uncertainty intersects with biological priorities. It is useful to consider SRS data uncertainty through a framework of error types analogous to type I and type II statistical errors. Type I errors (false positives) occur when SRS data indicate that conservation actions are feasible, when in fact they are not. Type II errors (false negatives) occur when SRS data indicate that conservation actions are not feasible, when in fact they are. Uncertainties that result in false negatives are more costly in terms of unsuccessful conservation actions, especially in areas of high biological priority. False positives may conversely result in inefficient use of resources. Conservation practitioners should therefore prioritize ground truthing to account for the likely impacts of these different types of errors and be guided by spatially explicit maps of SRS data uncertainty (Figure 3b).

It is also important to compare alternative approaches to including the social dimension of conservation planning such as land use modeling and participatory approaches (Figure 1). Participatory approaches to conservation planning may explicitly account for social values in conservation as a substitute for a spatial analysis where the focus is on the decision making process and building relationships rather than a final output from a model. For example, collective bargaining of the final location of protected areas (e.g. Game et al.

2011) may be a more effective way to ensure protected areas are implemented than selecting areas based on their predicted social acceptability (e.g. quantifying willingness to protect). However, this type of participatory planning may not be realistic for larger planning regions, where the number and diversity of stakeholders may make it too difficult to negotiate consensus.

Future research

The inclusion of elicited SRS data in conservation planning is a new and promising area of research that allows conservation planners to consider conservation opportunity. However, the dynamic nature of social systems, including their susceptibility to external shocks, can result in high level of uncertainty in SRS data, as we show here. Although ecological systems are also dynamic, social systems have the potential for very rapid change, for example when new information becomes available. When combining SRS data and biophysical data, the potential for uncertainty propagation is very real. Failure to explicitly account for this uncertainty could result in erroneous conservation priorities and feasibility of implementation could be reduced, counter to the desired outcomes from inclusion of the SRS data. Our typology for assessing SRS data uncertainty and the process we devised for more effectively managing uncertainty issues in conservation planning studies begin to address these concerns. Future research should explicitly consider whether inclusion of elicited SRS data has achieved desired outcomes of making conservation planning more implementable or if uncertainty outweighs the benefits of including SRS data.

Acknowledgements

This work was supported by the Australian Government's National Environmental Research Program through the Landscapes & Policy Research Hub and the Environment Decisions Hub. Additional support was provided through the ARC Centre of Excellence for Environmental Decisions.

Supporting Information

A version of figure 1 with examples (Appendix S1), extended definition of uncertainty (Appendix S2), spatial data graphical examples for figure 2 (Appendix S3), extended discussion of social data uncertainty (Appendix S4), extended discussion of spatial uncertainty associated with projecting SRS data (Appendix S5), review criteria and methods (Appendix S6), and complete references for Table 4 (Appendix S7) are available on-line. The authors are solely responsible for the content and functionality of these materials. Queries (other than absence of the material) should be directed to the corresponding author.

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Tables

Table 1: Geospatial characteristics of elicited spatially referenced social (SRS) data^a.

	Geospatial method				
	1. areal data –individual	2. areal aggregation ^b	3. areal data - predictive method	4. point pattern analysis (e.g., PPGIS)	5. local statistics (e.g. Kriging)
Example	landowners place values on their properties assets or willingness to sell of his/her property (Curran et al. 2012)	aggregated social data from multiple individuals such as census data; no example of elicited SRS data available	derive statistical relationship between social data and sub-catchment (Brouwer et al. 2010)	social or economic values individuals attach to multiple places on the landscape (Brown & Donovan 2013)	Kriged social data (Campbell et al. 2009)
Input data	n/a	points - quantitative	n/a	points - nominal	points – quantitative
Method of deriving value	Descriptive	descriptive	Statistical	descriptive	Statistical
Geospatial processing method	none	point to area	none	point to area	point to surface
Geographic unit	property boundary	areal - census boundary	areal – census area or catchment	areal - grid	areal – grid
Geospatial processing method description	associate individual social data with single spatial object (e.g., property)	derive descriptive statistic (e.g., mean) based on aggregation unit such as census district or government boundary	derive statistical relationship between landcover type and social data; non-spatial analysis undertaken and results projected spatially	point pattern analysis (e.g., identifying areas with high number of occurrences)	interpolate values between point locations.
Output data type	quantitative – continuous	quantitative – average (Gaussian)	quantitative – average (Gaussian)	quantitative – counts (binomial)	quantitative – fields or raster grid

^aSee Supporting Information for spatial data graphical examples.

^bThis type of analysis was included in this table even though it was not present in the review as it represents a very common type of geospatial analysis method used with social data.

Table 2. Types of social survey uncertainty.*

Type of uncertainty	Definition	Means of management	Tests to consider in social values studies (e.g. PPGIS)	Tests to consider in stated preference studies
Internal	confidence that the output shows what it is believed to show	research design controls, including validity testing	face validity content validity construct validity reliability	face validity content validity construct validity preference uncertainty
External	the confidence in the results being generalizable	research design controls, including validity testing	sample strategy and size representativeness concurrent validity predictive validity	preference uncertainty sample strategy and size representativeness concurrent validity predictive validity hypothetical bias

* Adapted from Haslam and McGarty (2001) (see Supporting Information for extended discussion).

Table 3. Types of spatial uncertainty associated with elicited spatially referenced social (SRS) data.

Type of uncertainty	Definition	Source	Potential methods to consider
Accuracy	Difference between measured value and true value	Social survey methodological uncertainty. Statistical model uncertainty	Simulate uncertainty in geographic units based on uncertainty bounds from social survey methodology or statistical model. Uncertainty quantified with statistical model e.g. standard errors and Bayesian approaches. Variations include Monte-Carlo methods, simulating the spatial distribution of uncertainty and local versus global sensitivity analysis
Change of support problem	Uncertainty due to the many ways of integrating different types of spatial data	Area to point - Ecological inference problem	Cross-classification with other variables, quadrat counts
		Point to area	Dasymetric mapping, use of areal centroids.
		Point to Surface	Geostatistical methods such as kriging, Cokriging
		Area to Area - the MAUP (e.g. combining multiple spatial datasets)	Areal interpolation; incompatible/misaligned zones, pixel aggregation, Bayesian areal regression models, multiscale spatial tree models and hierarchical models
		Area to Surface	Pycnophylactic interpolation

*See Supporting Information for extended discussion.

Table 4: Summary of papers on elicited SRS data describing the type of social data, the geospatial methods used and whether uncertainty is being addressed.

Reference^a	Conservation objectives	Social data	Method^b	Data gathering	Sample size	Geospatial Method	Data integration	Social data uncertainty^c	Spatial data uncertainty^c
Brouwer et al. 2010	water quality improvement	willingness to pay	choice experiment	interviews	619	Areal data Predictive	Overlay	yes	yes
Brown and Donovan. 2013	national forest planning	acceptable land uses	PPGIS	web survey	244 (11.6%)	Point pattern analysis	Overlay	no	no
Brown et al. 2004	biodiversity conservation	environmental values	PPGIS	mail survey and workshop interviews	542 (31%)	Point pattern analysis	Overlay	no	no
Bryan et al. 2010	ecosystem services	landscape social values and threats	PPGIS	interviews	84 (100%)	Point pattern analysis	Overlay	yes	no
Bryan et al. 2011	ecosystem services	social values for natural capital and ecosystem services and perceived threats	PPGIS	interviews	54	Point pattern analysis	Overlay	yes	no
Campbell et al. 2009	landscape improvement	willingness to pay	choice experiment	interviews	766 (78.33%)	Local statistics	Mapping	yes	yes
Curran et al. 2012	carbon credit restoration	willingness to sell or collaborate or participate, restoration opportunity and conservation related social values	standard survey	interviews	29	Areal data descriptive individual's property	Mapping	yes	no

Guerrero et al. 2010	expanding protected areas	willingness to sell	standard survey	interviews	48 (100%)	Areal data descriptive individual's property	SCP	yes	no
Knight et al. 2010	conservation action on private land	social values related to conservation success and willingness to collaborate	standard survey	interviews	48 (100%)	Areal data descriptive individual's property	SCP	yes	no
Knight et al. 2010	conservation action on private land	willingness to sell	standard survey	interviews	48	Areal data descriptive individual's property	SCP	yes	no
Pasquini et al. 2010	conservation on private land	willingness to steward	standard survey	interviews	50 (89%)	Areal data descriptive individual's property	Mapping	no	no
Raymond and Brown 2006	identifying future national park	landscape social values	PPGIS	mail survey	500	Point pattern analysis	Overlay	no	yes
Raymond and Brown 2011	climate change risks	landscape social values and perceived climate change risks	PPGIS	mail survey and workshop interviews	375 (61%)	Point pattern analysis	Overlay	yes	no
Raymond et al. 2009	ecosystem services	landscape social values and threats	PPGIS	mail survey	54	Point pattern analysis	Overlay	yes	no
Tyrväinen et al. 2007	open space values	landscape social values	PPGIS	mail survey	421 (42%)	Areal data descriptive individual's property	Mapping	yes	no
Whitehead et al. 2014	SCP with social and biological data	landscape social values	PPGIS	mail survey	395 (40%)	Point pattern analysis	SCP	yes	no

^aSee Supporting Information for full version of references.

^bPPGIS, public participation GIS.

^cWhether papers quantified or explicitly addressed one or more forms of uncertainty.

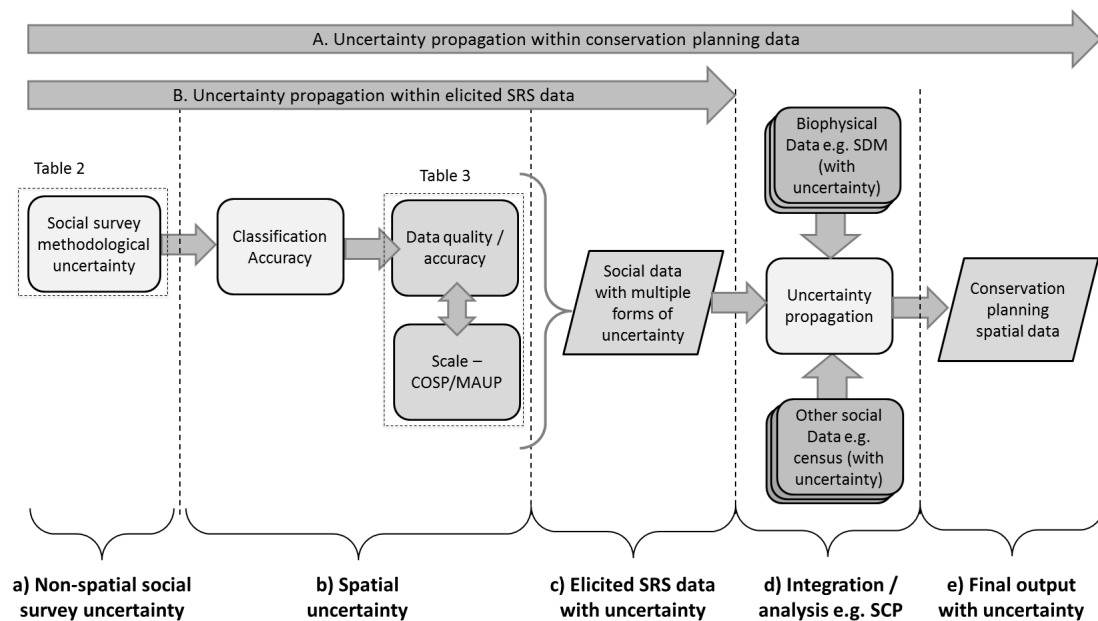


Figure 1. Methods for assigning preferences to spatially referenced social data (see Supporting Information for full version with examples) (dotted-line rectangle, scope of review).

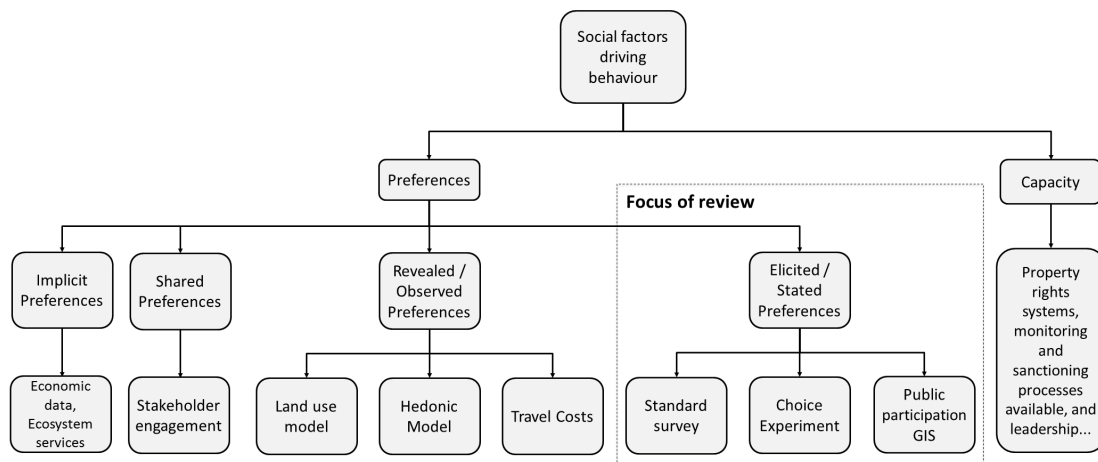
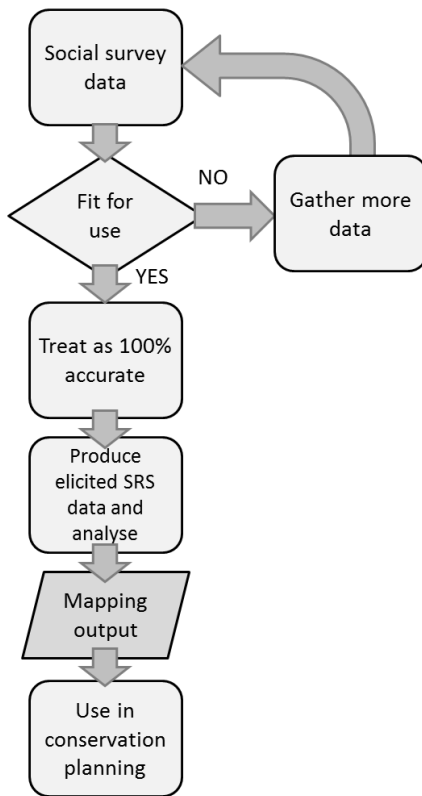


Figure 2. Conceptual diagram describing the steps in the processing and analysis of elicited spatially referenced social (SRS) data and the propagation of non-spatial methodological uncertainty and spatial uncertainty (COSP, change of support problem; MAUP, modifiable areal unit problem) and combining with other forms of data (e.g. SDM, species distribution model). Uncertainty propagation can be tested in the production of elicited SRS data and/or for the outputs of a spatial analysis for conservation planning.

a) Current



b) Proposed

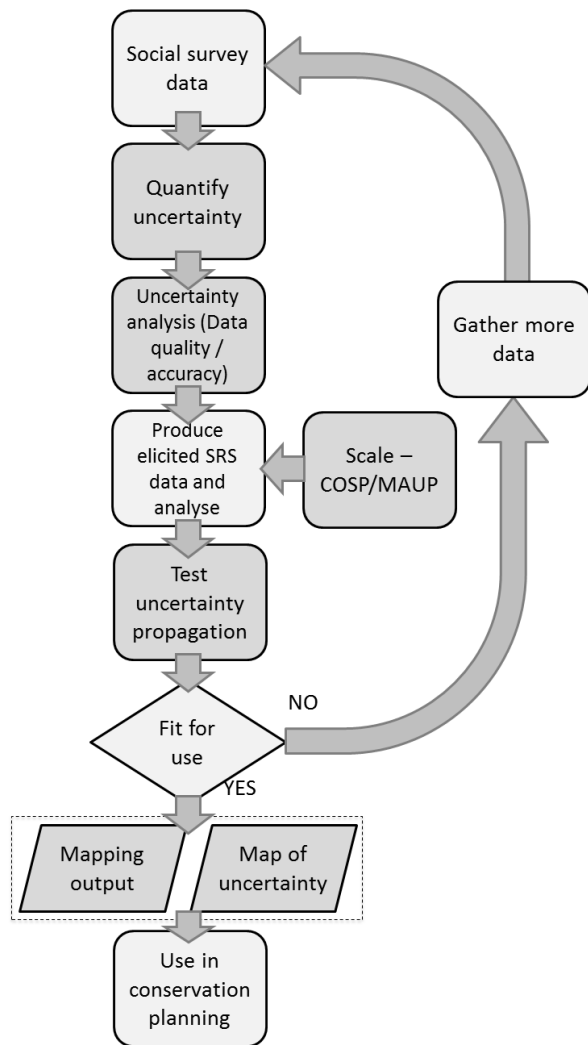


Figure 3. Process for addressing uncertainty in elicited spatially referenced social (SRS) data: (a) current method used in producing elicited SRS data and (b) suggested method for dealing with uncertainty (COSP, change of support problem; MAUP, modifiable areal unit problem).